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Projecting the Effects of Climate Change on Water irrigation needs for Maize Production Systems Using the LARS-WG and Hargreaves Method

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Abstract. The production of food crops is severely hampered by climate change, which is characterized by rising temperatures and changes in precipitation. This is especially true for maize, a cornerstone of Indonesia's food security. This study aims to forecast future climatic conditions over the next two decades and estimate the resulting irrigation water demands for maize cultivation in East Java, West Sumatra, and North Maluku. Future climate scenarios were generated using the LARS-WG model, which incorporated the HadGEM3-GC31-LL General Circulation Model and three CMIP6 pathways (SSP126, SSP245, and SSP585). The Hargreaves method was then applied to calculate reference evapotranspiration and, subsequently, crop irrigation requirements. To validate the model's reliability, historical climate data (2004–2023) was analyzed using the Kolmogorov-Smirnov, t-test, and f-test at an $\alpha = 0.05$ significance level. Model calibration and evaluation were conducted using the R^2, MSE, and RMSE metrics. The results show that LARS-WG effectively simulated local climate variables, and the evapotranspiration estimates were consistent with regional characteristics. The analysis revealed that while temperature has a positive correlation with irrigation demand, effective precipitation has a negative one. Furthermore, mean temperature and effective precipitation showed no significant direct effect on maize yields, whereas extreme temperatures had a minor impact. These findings suggest that future climate

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scenarios could increase irrigation needs, highlighting the necessity for adaptive management of water resources strategies.

1 Introduction

The agricultural sector is under significant stress from climate change, driven largely by shifting temperature and rainfall patterns that directly affect crop growth [1]. Maize, a vital commodity for Indonesia's food security, is particularly susceptible to these shifts. The urgency of this issue is underscored by recent data from 2023, which showed a 12.5% decline in national maize production to 14.46 million tons. This drop, coupled with a rise in domestic consumption to 15.7 million tons, led to a 7.92% reliance on imports. These figures highlight the critical need to incorporate climate change factors into any strategy designed to maintain and boost maize yields.

A substantial body of research has explored how climate change affects maize farming. It is well-established that variations in temperature and precipitation have a direct impact on both the timing of planting and final yield outcomes. Maize thrives within an optimal temperature window of roughly 25 to 33°C. When temperatures rise above this, they can hasten the plant's development, especially during the crucial reproductive phase. This acceleration shortens the overall growing cycle and can lead to diminished harvests. Additionally, the combination of higher temperatures and longer sunny periods can ramp up transpiration, elevating the likelihood of water stress in the plants [2-4].

As highlighted by Sura et al. [5], precise water management across all growth stages is essential for maximizing maize yields. The crop's water demand is particularly high during the flowering and grain-filling periods. In Indonesia's tropical climate, the water requirement for a single growing season typically falls between 236 and 276.9 mm, averaging about 256.5 mm. Given this, it is crucial to project future water availability using climate-based models. Such projections are key to developing adaptive irrigation strategies that can sustain the production of maize in light of climate change.

For this study, future climate scenarios for the 2025–2044 period were generated using the LARS-WG model. This tool was chosen based on findings by Mehan et al. [6], which showed its superior performance over other stochastic weather generators like CLIGEN. Its effectiveness has been demonstrated in numerous climate and water resource studies across tropical and subtropical zones [7, 8]. LARS-WG refines its projections by integrating data from General Circulation Models (GCMs), which replicate the world's climate processes. For this analysis, the HadGEM3-GC31-LL GCM was selected for its proven ability to accurately represent tropical climate dynamics [9]. The model also incorporates the latest Coupled Phase 6 of the Model Intercomparison Project (CMIP6) framework, using Shared Socioeconomic Pathways (SSP) to simulate various predictions of the future climate based on various greenhouse gas concentration trajectories—specifically SSP126 (low), SSP245 (moderate), and SSP585 (high) [10].

Reference evapotranspiration is estimated using the Hargreaves method, which is recognized as a reliable temperature-based approach [1]. Compared to the Penman–Monteith method, the Hargreaves equation requires fewer input parameters and performs well in areas with limited climatic data availability. This method has been extensively used in evapotranspiration estimation and water resource management studies in tropical and subtropical countries. The SSP scenarios applied in this study consist of SSP126 (low emission pathway), SSP245 (moderate emission pathway), and SSP585 (high emission pathway) [2].

In addition, water irrigation needs are calculated to support improved water resource management [1]. The goals of this research are: (1) to estimate maize water irrigation needs using the Hargreaves method; (2) using LARS-WG to forecast future climate conditions using local climate data that has been seen.; and (3) to examine how climate factors affect the need for irrigation and the yield of maize. This approach is expected to contribute to the advancement of climate-resilient agricultural systems and adaptive irrigation management in Indonesia and other tropical areas.

2 Material and Methods

2.1 The research site's description

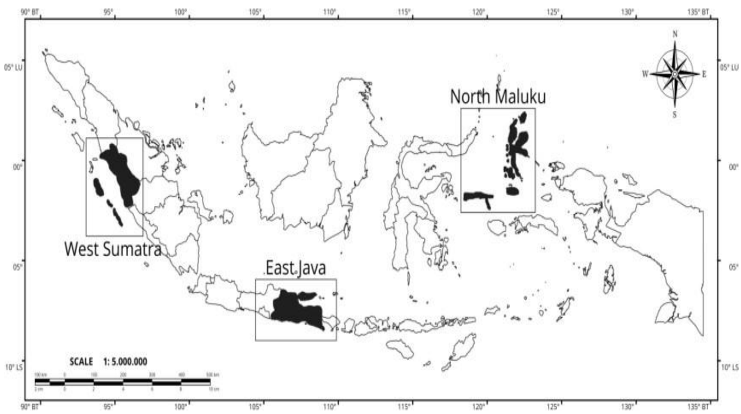


Fig. 1. The Research Site

The study concentrated on three provinces (East Java, West Sumatra, and North Maluku) as they reflect significant contrasts in both their roles in national maize production and their climatic profiles, symbolizing the eastern, central, and western parts of Indonesia. According to data from Central Statistics Agency (2025), maize output in 2024 amounted to 4.59 million tons in East Java, 518 thousand tons in West Sumatra, and just 4.5 thousand tons in North Maluku. These marked differences are strongly associated with regional climate variability, particularly in terms of temperature and rainfall patterns, which affect cropping systems and yield performance [5]. Therefore, the inclusion of these three provinces offers a robust framework for assessing Climate change's effects on water irrigation needs and maize productivity across diverse agroclimatic regions of Indonesia.

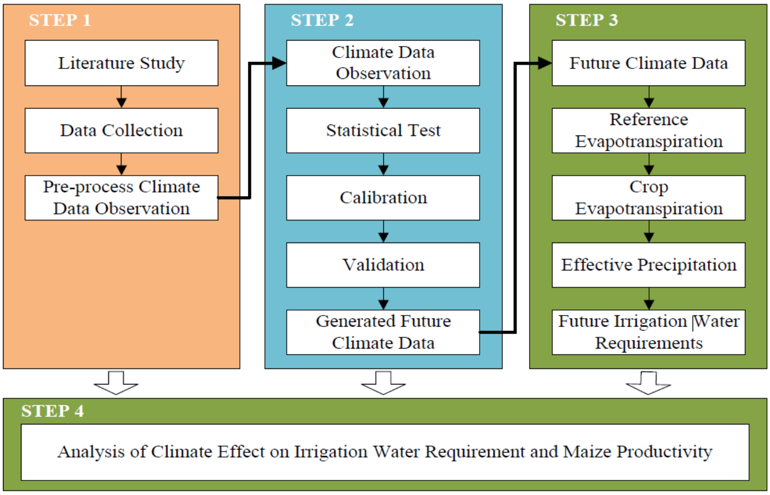


Fig. 2. Study framework

2.2 Data from Research

Meteorological data for each day for the research locations in East Java, West Sumatra, and North Maluku were obtained from the Meteorology, Climatology, and Geophysics Agency. The dataset spans a 20-year period (2004–2023) and comprises minimum temperature (°C), maximum temperature (°C), daily rainfall (mm/day), and solar radiation duration (hours/day). Additionally, maize productivity data (tons/ha) for the same time frame were sourced from the Central Statistics Agency for each respective site. Crop evapotranspiration of maize was calculated using crop coefficient (Kc) values established in this study, categorized into four growth phases: initial (0.48), development (0.99), mid-season (1.38), and late season (0.62).

Before conducting the analysis, the observed climate data from each site were pre-processed using Microsoft Excel 2010. The data were then formatted to comply with the input specifications of the LARS-WG model, with daily records arranged into the following variables: Duration of Solar Radiation, Year, Month, Day, Minimum and Maximum Temperatures, and Precipitation.

2.3 Future Climate Data Generated

Observed climate data were used as the primary input at this stage, where statistical comparisons were carried out between the simulated climate outputs and the corresponding observed records. These statistical procedures are integrated within the LARS-WG software and consist of the Kolmogorov–Smirnov (K–S) test to compare probability distributions, the t-test to detect differences in mean values, and the f-test to evaluate variance differences. All analyses were conducted at a significance level of $\alpha = 0.05$. If the resulting p-value was greater than α, the simulated and observed datasets were considered statistically consistent, indicating that the LARS-WG model was able to satisfactorily reproduce the observed climate characteristics.

In order to evaluate the performance of the model, the 20-year dataset was split equally between calibration (2004–2013) and validation (2014–2023) [6]. The Coefficient of Determination (R2), Mean Squared Error (MSE), and Root Mean Square Error (RMSE) were used to assess the model's accuracy in both phases. This procedure ensured that LARS-WG could reliably represent local climatic conditions before being utilized for future climate projections. The outcomes of the calibration and validation processes determined the model's suitability for generating projected climate data at each study location in West Sumatra, North Maluku, and East Java.

After achieving satisfactory calibration and validation results, daily climate projections for the 2025–2044 period were generated using LARS-WG under the CMIP6 emission scenarios, namely SSP126 (low emissions), SSP245 (intermediate emissions), and SSP585 (high emissions). Within the LARS-WG framework, these scenarios emphasize atmospheric carbon dioxide (CO_2) concentrations and are derived from outputs of the HadGEM3-GC31-LL Global Climate Model (GCM) [16]. Solar radiation (MJ/m²/day), rainfall (mm/day), minimum temperature (°C), and maximum temperature (°C) are among the predicted climate variables. These projections were subsequently utilized to estimate maize water irrigation needs and to examine the impacts of climate variability on irrigation demand and maize productivity across the three study regions.

2.4 Future Needs for Irrigation Water

To determine future irrigation demands, the study first calculated reference evapotranspiration (ETo) using the temperature-based Hargreaves equation, as outlined by Akhavan et al. [1]:

$$ET_o = 0{,}408 \times 0{,}0025 \times (T_{mean} + 16{,}8) \times (\Delta T)^{0{,}5} \times R \quad (1)$$

Where:
T = average temperature per day (°C)
ΔT = represents the daily temperature range (°C)
R = solar radiation (MJ/m² day).

Crop evapotranspiration (ETc), which represents the total water used by the maize crop, was then derived by multiplying ETo by a crop coefficient (Kc) specific to each growth stage [3]:

$$ET_C = Kc_{maize\ growth\ phase} \times ET_O \quad (2)$$

The Kc values used were 0.48 for the initial stage, 0.99 for the development stage, 1.38 for the mid-season stage, and 0.62 for the late-season stage.

The portion of rainfall that is usable by the crop, known as Precipitation effective (Pe), was calculated from daily rainfall data (P) using the following USDA Soil Conservation Service method [3]:

$$if\ P \leq 250\ mm : Pe = P/125 \times [125 - (0{,}2 \times P)] \quad (3)$$

$$if\ P > 250\ mm : Pe = 125 + (0{,}1 \times P) \quad (4)$$

Finally, the irrigation water requirement (IWR) was determined as the difference between the crop's total need and the water supplied by effective rainfall [1, 13] :

$$IWR = ETc - Pe \quad (5)$$

In cases where effective precipitation was sufficient to meet or exceed the crop's demand ($Pe \geq ETc$), the IWR was set to zero, indicating no need for supplemental irrigation [7].

2.5 Examination of the Impact of Climate Change on Irrigation

A correlation technique was used to determine the degree and direction of the relationship between important environmental factors (temperature and rainfall) and water irrigation needs in order to examine the relationship between irrigation demand and maize production. Estimated irrigation demand for East Java, West Sumatra, and North Maluku between 2025 and 2044 was combined with forecasted climate scenarios. Trend graphs are used to describe the findings and show how irrigation Needs in each research area are influenced by climatic factors.

Moreover, the impact of precipitation and temperature on maize productivity was assessed using the polynomial regression method. This assessment integrated observed maize yield data from 2004 to 2023 in the three regions with anticipated climatic data. The findings and the coefficient of determination (R2), which shows the percentage of yield variability at each site that can be attributed to climatic variables, are presented in scatter diagrams fitted with second-order polynomial curves.

3 RESULTS AND DISCUSSION

3.1 Climate Projections for the Future

3.1.1 Statistical Test (K-S Test, T-test, and f-test)

A statistical comparison between the observed and LARS-WG simulated climate data for West Sumatra, North Maluku, and East Java revealed consistent distribution patterns. The Kolmogorov-Smirnov (K-S) test (Table 1) confirmed that all climate variables—minimum temperature, maximum temperature, and precipitation—follow a normal distribution. Furthermore, the t-test results (Table 2) indicated no statistically significant difference between the mean values of the observed and simulated datasets. These findings align with the work of Kavwenje et al. [2], who also reported that LARS-WG effectively preserves the statistical properties of local climate records.

The f-test was used to compare variances. The results (Table 3) showed that the standard deviations for temperature were very low, indicating that the simulated data points are tightly clustered around the mean. For monthly rainfall, the model's simulated standard deviations were slightly lower than the observed values, suggesting a minor underestimation of variability. However, this is a common and generally acceptable outcome in LARS-WG applications, as noted in multiple studies [3, 8]. Overall, the statistical tests confirm that the LARS-WG model is well-suited for generating reliable climate projections for the three study areas.

Table. 1 p-value Kolmogorov-Smirnov Test

Month	p-value K-S test								
	East Java			West Sumatra			North Maluku		
	MIN	MAX	RAIN	MIN	MAX	RAIN	MIN	MAX	RAIN
Jan	1,000	1,000	0,966	1,000	1,000	0,913	1,000	1,000	0,937
Feb	1,000	1,000	1,000	0,999	1,000	0,994	0,913	1,000	0,732
Mar	1,000	1,000	1,000	1,000	1,000	0,994	0,999	0,999	1,000
Apr	1,000	1,000	0,971	1,000	1,000	0,998	1,000	1,000	1,000
May	0,999	1,000	1,000	1,000	1,000	1,000	1,000	0,999	1,000
Jun	0,999	0,999	0,837	0,999	1,000	0,578	0,999	1,000	0,993
Jul	1,000	1,000	1,000	1,000	1,000	1,000	0,999	0,999	1,000
Aug	0,637	1,000	0,537	0,913	1,000	1,000	0,999	1,000	1,000
Sep	0,913	1,000	0,215	1,000	1,000	0,589	0,913	1,000	0,749
Oct	0,999	0,999	1,000	1,000	1,000	1,000	0,913	1,000	1,000
Nov	0,999	1,000	1,000	0,999	1,000	1,000	0,631	1,000	1,000
Dec	0,999	1,000	1,000	1,000	1,000	1,000	0,913	1,000	1,000

Note : MIN = minimum; MAX = maximum; RAIN = precipitation

Table. 2 p-value t- test

Month	p-value t- test								
	East Java			West Sumatra			North Maluku		
	MIN	MAX	RAIN	MIN	MAX	RAIN	MIN	MAX	RAIN
Jan	0,364	0,194	0,690	0,887	0,212	0,610	0,899	0,898	0,530
Feb	0,418	0,706	0,838	0,839	0,481	0,619	0,798	0,649	0,529
Mar	0,937	0,400	0,293	0,168	0,948	0,329	0,915	0,363	0,342
Apr	0,673	0,355	0,370	0,462	0,898	0,505	0,945	0,569	0,631
May	0,196	0,471	0,148	0,338	0,516	0,071	0,973	0,458	0,904
Jun	0,646	0,583	0,340	0,834	0,789	0,578	0,928	0,886	0,469
Jul	0,221	0,633	0,681	0,897	0,677	0,963	0,758	0,324	0,936
Aug	0,102	0,379	0,304	0,041	0,807	0,915	0,688	0,855	0,070
Sep	0,151	0,974	0,647	0,470	0,979	0,584	0,500	0,664	0,992
Oct	0,698	0,425	0,425	0,485	0,973	0,627	0,833	0,942	0,539
Nov	0,922	0,748	0,969	0,655	0,535	0,677	0,748	0,863	0,406
Dec	0,999	0,882	1,000	1,000	1,000	1,000	0,738	0,835	0,411

Note : MIN = minimum; MAX = maximum; RAIN = precipitation

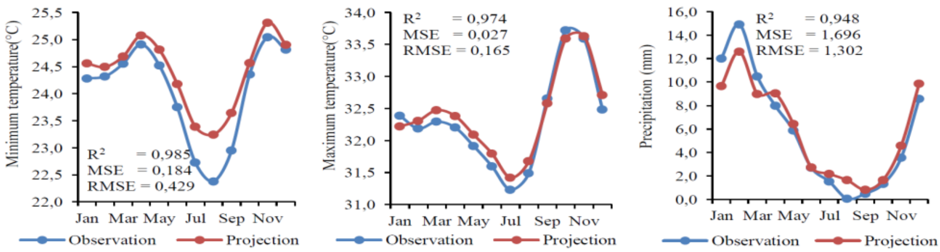
Table. 3 p-value f- test

Month	p-value f- test								
	East Java			West Sumatra			North Maluku		
	MIN	MAX	RAIN	MIN	MAX	RAIN	MIN	MAX	RAIN
Jan	2,3E-07	8,7E-05	0,090	2,2E-05	5,9E-04	0,121	8,7E-12	2,9E-07	0,115
Feb	1,0E-05	3,2E-03	0,313	6,0E-05	4,6E-02	0,059	2,3E-09	4,4E-03	0,179
Mar	1,6E-03	1,0E-04	0,419	5,0E-05	1,8E-05	0,442	5,3E-09	1,1E-05	0,184

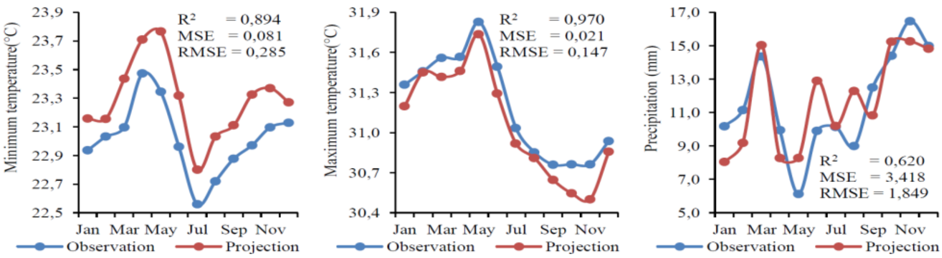
Apr	1,9E-03	1,6E-05	0,316			0,036	2,6E-10		0,217
May	3,2E-06	9,1E-05	0,163	1,6E-05	1,7E-04	0,090	1,0E-10	9,7E-06	0,013
Jun	2,4E-06	1,9E-05	0,489	8,6E-03	1,3E-02	0,266	4,1E-09	2,7E-03	0,386
Jul	1,5E-06	2,0E-08	0,201	1,8E-03	6,3E-04	0,141	2,7E-11	7,1E-04	0,037
Aug	5,1E-07	7,6E-08	0,004	2,7E-04	2,8E-03	0,319	6,1E-10	7,9E-07	0,011
Sep	6,3E-08	5,0E-08	0,474	4,7E-05	5,7E-04	0,006	3,7E-07	1,6E-06	0,049
Oct	3,6E-05	2,2E-04	0,008	1,1E-05	5,0E-07	0,214	9,3E-08	2,3E-04	0,262
Nov	3,3E-03	4,0E-05	0,209	6,3E-06	7,0E-04	0,201	1,5E-10	5,6E-05	0,368
Dec	2,0E-05	6,9E-07	0,149	1,3E-04	2,7E-04	0,401	2,3E-12	7,4E-04	0,122

Note : MIN = minimum; MAX = maximum; RAIN = precipitation

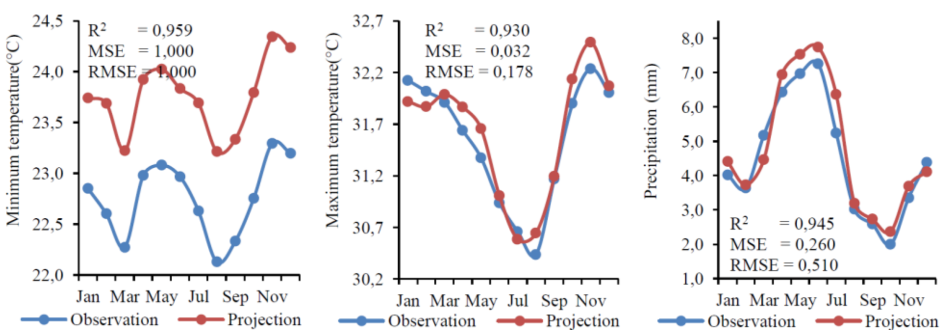
3.1.2 Calibration and Validation



Note: East Java climatic



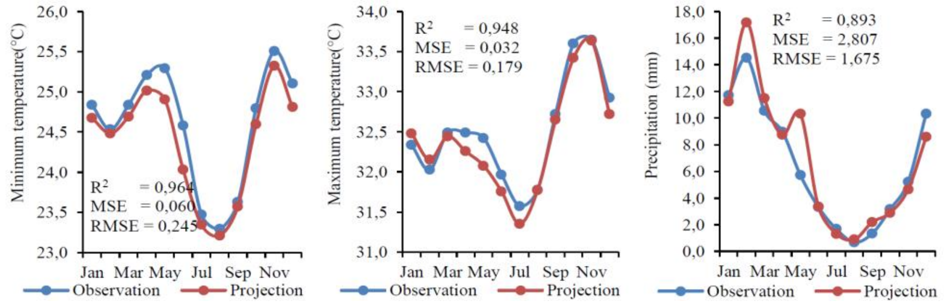
Note: West Sumatra climatic



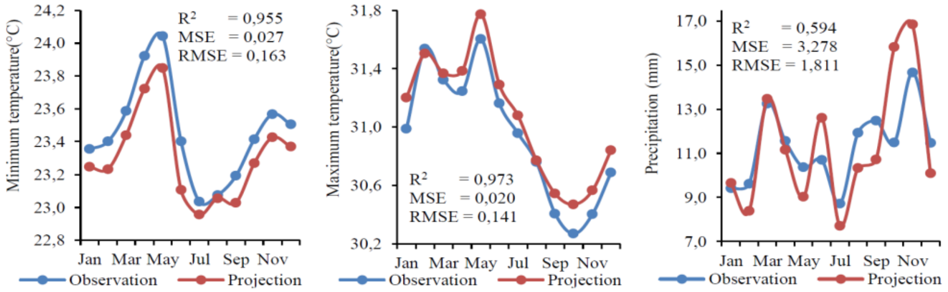
Note: North Maluku climatic

Fig. 3. Calibration result of the LARS-WG model

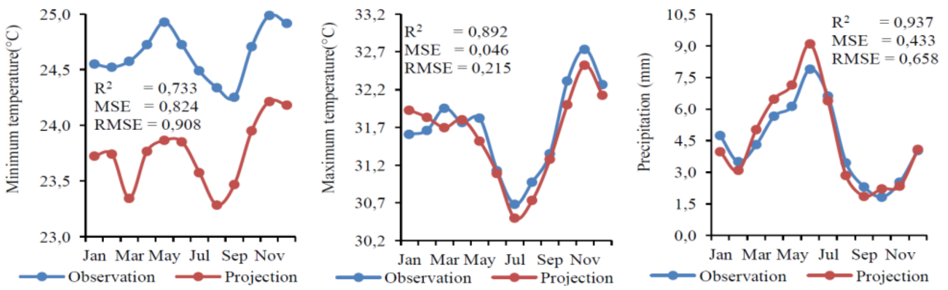
Based on comparisons with actual climate data from 2004 to 2013 and shown in Fig. 3, the LARS-WG model's calibration results show that the model does a good job of replicating past climatic patterns at the three study sites. It accurately depicts rainfall variability as well as the trends and variations of minimum and maximum temperatures. With low error rates between 0.1 and 1.8 and an agreement between simulated and actual data ranging from 62% to 98%, the model accuracy is deemed satisfactory.



Observe: East Java climatic



Observe: West Sumatra climatic



Observe: North Maluku climatic

Fig. 4. Validation result of the LARS-WG model

The validation results, which are shown in Fig. 4, complement the previous calibration findings and demonstrate how well the model reproduces historical climate conditions in the three research areas. With agreement levels ranging from 59% to 97% and comparatively tiny error values between 0.1 and 1.8, the simulated temperature and precipitation data throughout the 2014–2023 validation period closely matched the observed records. These findings support the findings of Kavwenje et al. (2022) and show that LARS-WG is capable of accurately capturing local climate features. As a result, the model is regarded as trustworthy for producing estimates of the future climate [2].

3.1.3 Forecasts for the Cilmate Future

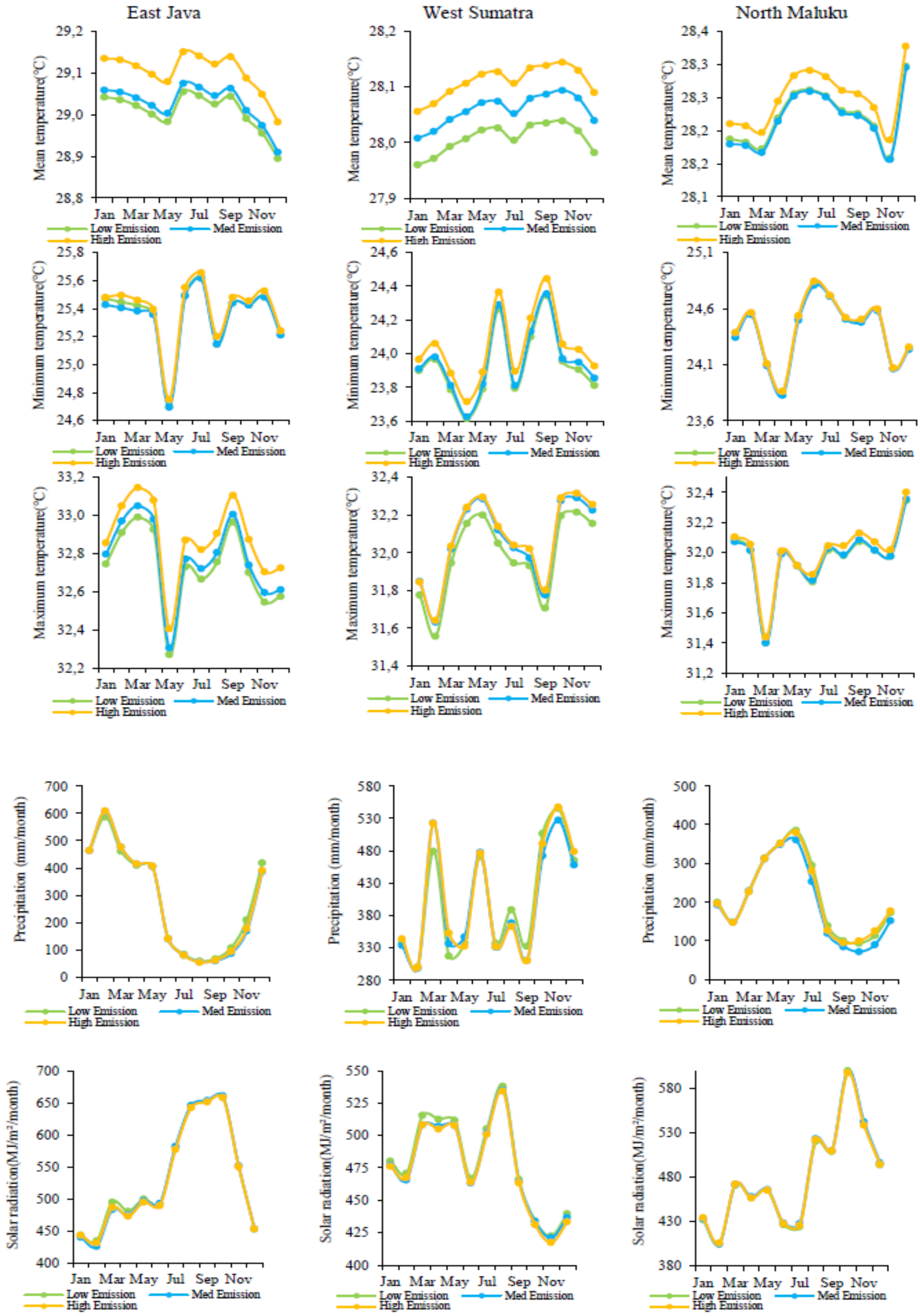


Fig. 5. Forecasts climate future

Consistent with previous research findings [2–8], forecasts generated under the three CMIP6 paths show only minor changes (Fig. 5). Different levels of greenhouse gas emissions, particularly carbon dioxide (CO_2), are the primary cause of the differences between scenarios [8]. However, because regional processes like the Asia-Australia monsoon circulation and the El Niño-Southern Oscillation have a greater influence on climate variability than short- to medium-term global emission changes, climatic reactions in tropical regions typically happen more slowly. Additionally, as noted by Kavwenje et al. (2022), the comparatively short projection horizon adds to the restricted diversity between scenarios.

Monthly minimum temperatures in East Java show seasonal variations. Since more clouds block down incoming solar radiation during the rainy season, lower minimum temperatures are usually observed. Maximum temperatures also exhibit seasonal variation, typically being greater during the dry season when the intensity of solar radiation is enhanced by clearer skies [9]. There is a clear monsoonal pattern to precipitation, with the rainy season lasting from December-May and the dry season lasting from June-November. This cycle is reflected in solar radiation, which rises during the dry months and falls during the rainy season when cloud development prevents sunlight from penetrating.

In contrast, West Sumatra's lowest and maximum temperatures fluctuate throughout the year. The distribution of rainfall is more unpredictable, which lessens the contrast between dry and rainy times. This inconsistency highlights the necessity for effective water management measures by raising the possibility of seasonal water shortages. Seasonality also affects solar radiation, which peaks in August and troughs in November.

Maximum temperatures in North Maluku are rather constant, although minimum temperatures fluctuate throughout the year. The effect of increased solar radiation during the dry season is demonstrated by the fact that the maximum temperature fluctuates the least in March and then gradually increases until December [9]. With a wet phase from March-June and a dry period from July-February, rainfall shows a distinct seasonal rhythm. Similar to this, solar radiation decreases during the rainy season as cloud cover lessens the strength of the sun's rays.

3.2 Estimation of Water Irrigation Needs

3.2.1 Reference Evapotranspiration (ETo)

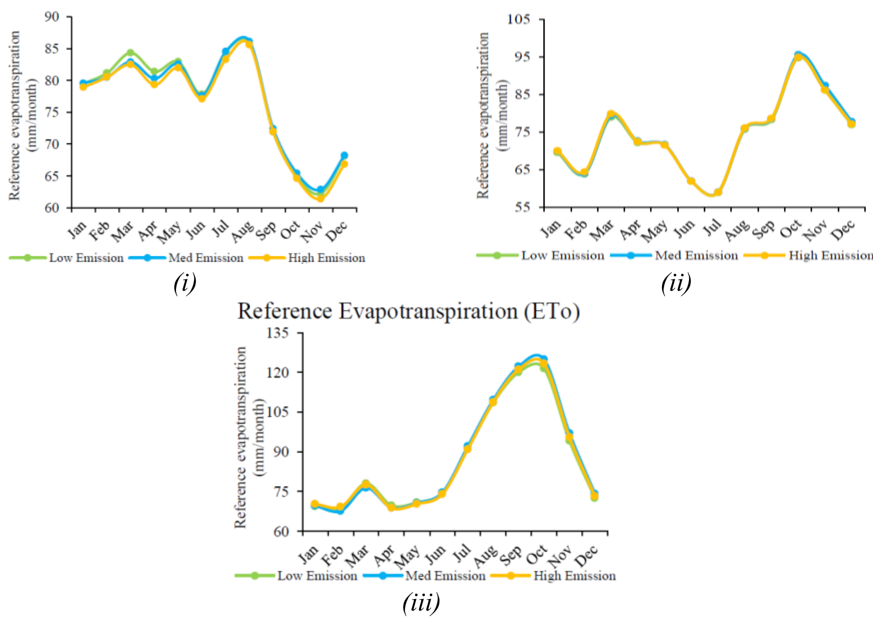


Fig. 6. Use the Hargreaves technique to reference evapotranspiration; (i) West Sumatra; (ii) North Maluku; (iii) East Java

As illustrated in Fig. 6, reference evapotranspiration (ETo) exhibits distinct seasonal patterns across all study locations. In both East Java and North Maluku, ETo values decline during the wet season (December-May) and increase throughout the dry season (June-November). Conversely, West Sumatra displays a relatively stable ETo pattern at the beginning of the year, reaching its maximum in August before gradually decreasing toward year-end. This seasonal behavior is attributable to higher temperatures and increased solar radiation during dry periods, which accelerate moisture loss from soil and plant surfaces. During the rainy season, cooler conditions and reduced solar radiation lead to lower evapotranspiration rates and consequently lower ETo values. Overall, these findings demonstrate that the Hargreaves method effectively captures the seasonal variations in reference evapotranspiration consistent with each region's distinctive climatic characteristics.

3.2.2 Precipitation effective (Pe) and Crop Evapotranspiration (ETc)

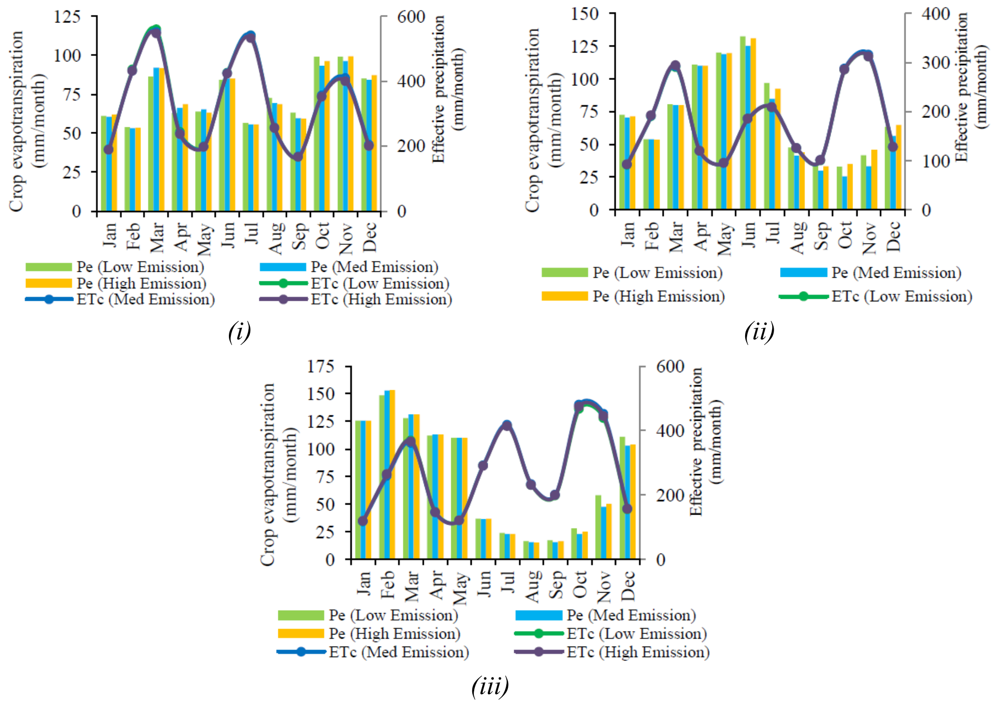


Fig. 7. Precipitation Effective and crop evapotranspiration; (i) West Sumatra; (ii) North Maluku; (iii) East Java

Figure 7 presents the precipitation effective (Pe) and crop evapotranspiration (ETc) values for the three study areas, revealing the dynamic interplay between water demand and supply across three annual planting cycles. Consistent with Suharjito et al. [10], peak ETc values occur during the transition from the development to the mid-season stage—typically in March, July, and November—coinciding with flowering and cob formation. During these critical periods, the crop coefficient (Kc) reaches its maximum, reflecting heightened water demand as the ratio of crop to reference evapotranspiration increases.

Each region experiences its highest effective precipitation during the rainy season, although the timing and intensity vary by location. Effective rainfall plays a vital role in supporting crop development, as maize requires adequate moisture throughout all growth phases. As emphasized by Sura et al. [11], precise water management during key developmental stages—particularly vegetative growth and cob formation—is essential for optimizing plant health and maximizing grain yield.].

3.2.3 Water irrigation needs

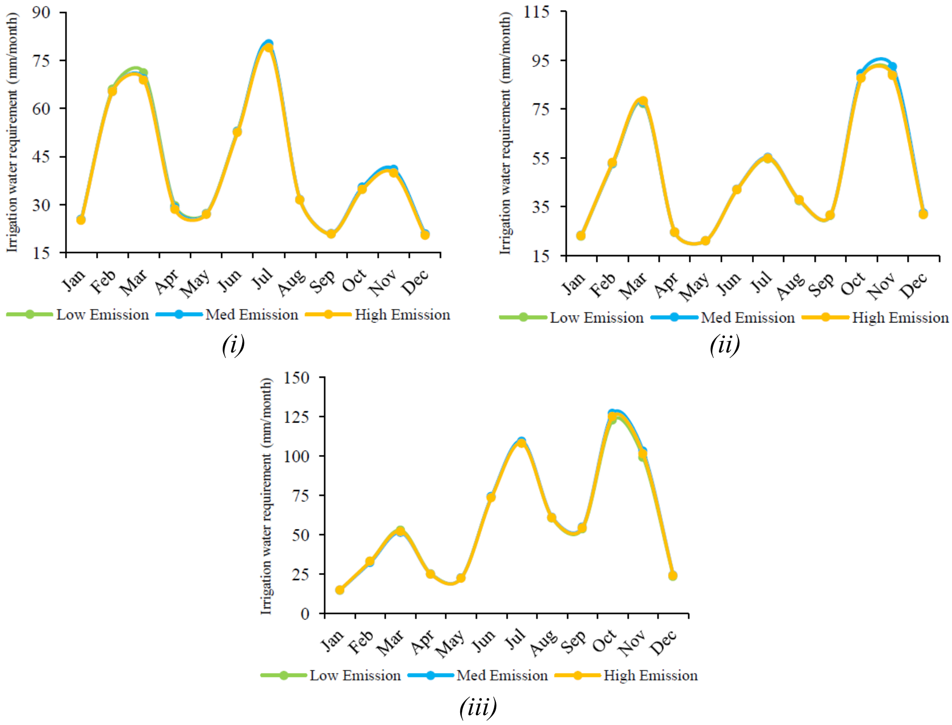


Fig. 8. Water Irrigation Needs; (i) West Sumatra; (ii) North Maluku; (iii) East Java

The temporal variation in irrigation water requirements across the three provinces, depicted in Fig. 8, results from the combined influence of climatic conditions and maize growth stages. During the dry season, elevated temperatures, increased solar radiation, and reduced rainfall drive higher evapotranspiration rates, thereby increasing irrigation demand. Conversely, during the wet season, irrigation serves as a supplementary water source when rainfall alone proves insufficient to meet crop needs [11].

As noted by Suharjito et al. [10], irrigation requirements are shaped by both environmental factors and the plant's phenological stage. Water consumption rises substantially during flowering and cob development in contrast to the initial stages of planting or harvesting, owing to heightened transpiration activity. These findings underscore the importance of adjusting planting schedules and implementing efficient irrigation practices to achieve optimal maize productivity.

3.3 Analysis of Climate Effect on Water Irrigation Needs

3.3.1 Average Temperature to irrigation needs

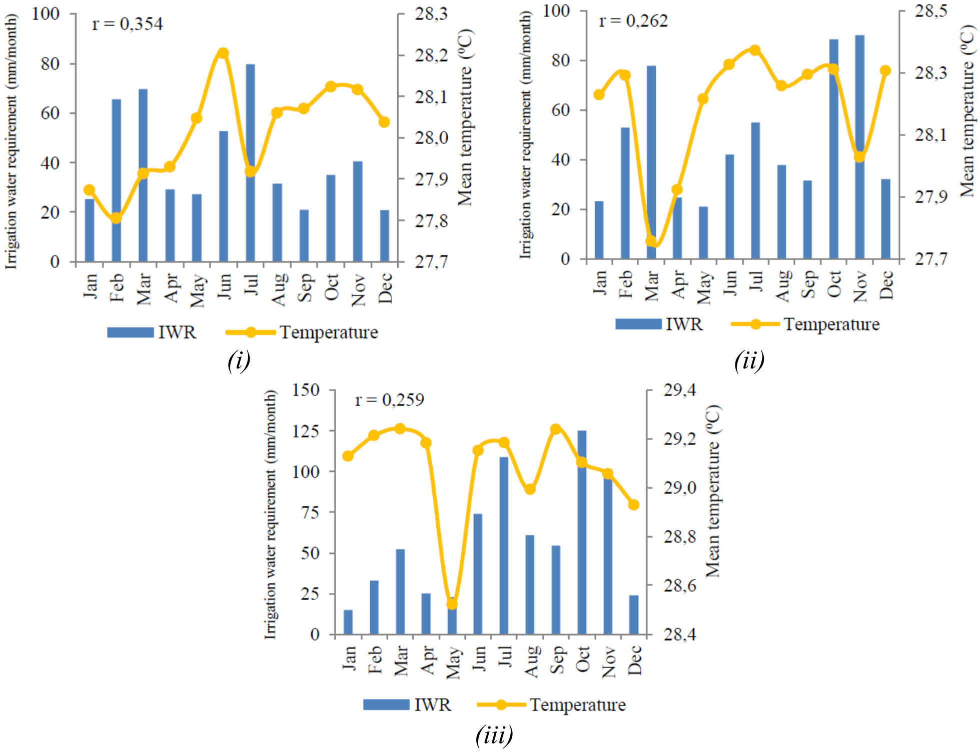


Fig. 9. Relationship temperature and water irrigation Needs; (i) West Sumatra; (ii) North Maluku; (iii) East Java

Figure 9 reveals a modest positive correlation between mean temperature and irrigation water demand across all three study areas. This relationship indicates that rising temperatures—particularly during the dry season—tend to increase irrigation needs by accelerating evapotranspiration rates [11]. However, exceptions exist, such as in East Java from January through April, where higher temperatures coincide with lower irrigation requirements. This anomaly occurs because these months fall within the rainy season, during which abundant rainfall adequately satisfies crop water demands, thereby reducing reliance on irrigation. This observation aligns with findings by Nie et al. [12], who reported that the influence of temperature on irrigation demand diminishes during wet periods when natural water availability is sufficient.

3.3.2 Influence of highst Temperature to Irrigation Needs

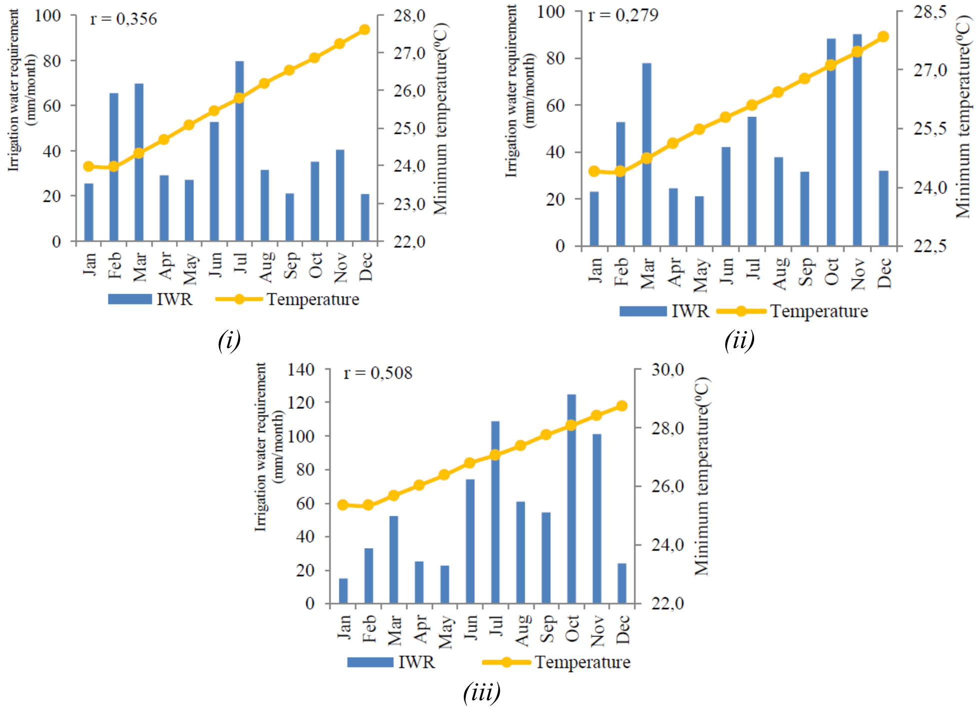


Fig. 10. Correlation low temperature and water irrigation Needs; (i) West Sumatra; (ii) North Maluku; (iii) East Java

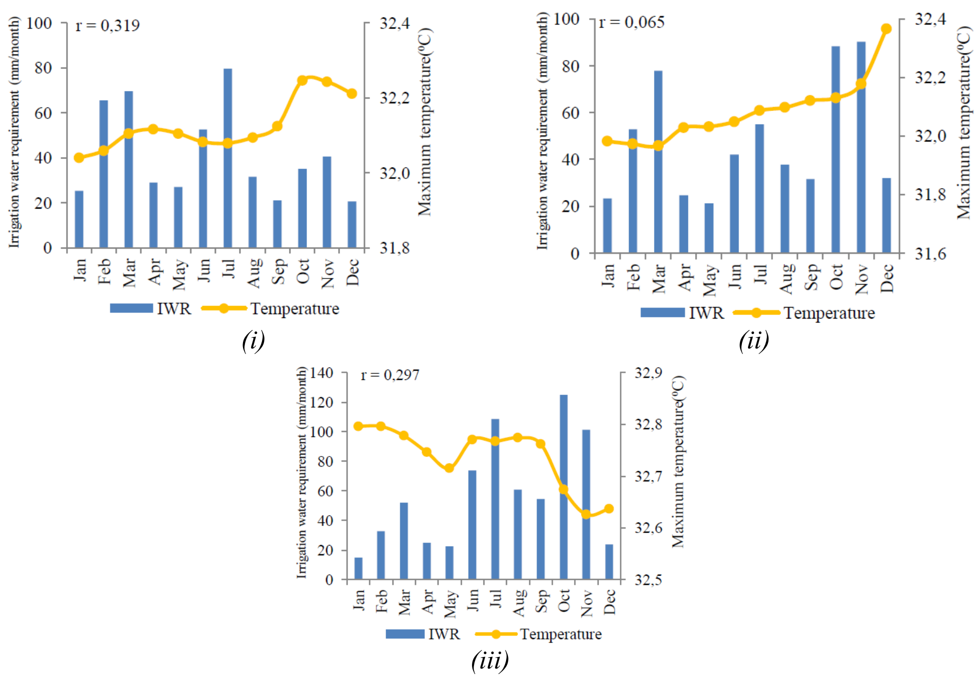
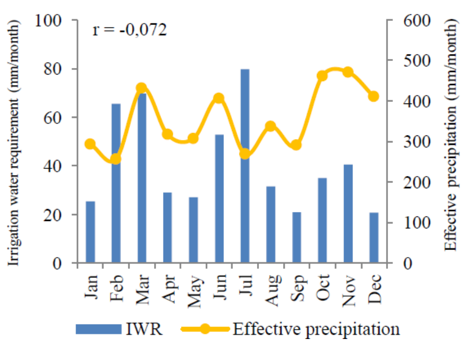


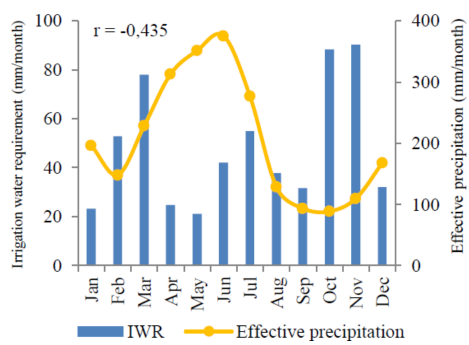
Fig. 11. Correlation high temperature and water irrigation Needs; (i) West Sumatra; (ii) North Maluku; (iii) East Java

To evaluate the influence of temperature extremes on irrigation demand, both minimum and maximum temperatures were analyzed. The correlation strengths ranged from weak to moderate, as shown in Figs. 10 and 11, with minimum temperature exhibiting a stronger relationship with irrigation water requirements than maximum temperature. This disparity can be attributed to the Hargreaves evapotranspiration method, which incorporates the daily temperature range (difference between maximum and minimum) as a key input variable [1]. Since minimum temperature directly influences this range, larger diurnal variations lead to higher estimated evapotranspiration and consequently greater irrigation demand [11]. In tropical climates, maximum temperatures remain relatively stable throughout the year, limiting their impact on evapotranspiration calculations and resulting in a weaker correlation with irrigation needs [8].

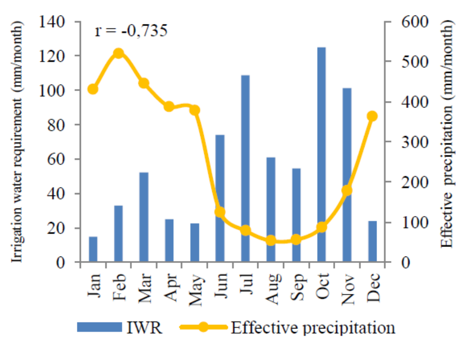
3.3.3 Effective Precipitation to irrigation needs



(i)



(ii)



(iii)

Fig. 12. Correlation effective precipitation and water irrigation needs; (i) West Sumatra; (ii) North Maluku; (iii) East Java

Figure 12 illustrates a negative correlation between precipitation effective (Pe) and irrigation water requirements (IWR), with the strength of this relationship varying across regions. As precipitation increases, particularly during the rainy season, irrigation demand generally decreases because rainfall effectively meets crop water needs [11]. The observed variability in correlation strength reflects differences in regional climatic conditions. According to Nie et al. [12], the relationship between precipitation and irrigation demand tends to weaken in consistently humid areas where natural rainfall regularly satisfies crop requirements. This pattern is evident in West Sumatra, which receives higher annual rainfall compared to East Java and North Maluku, resulting in a weaker correlation between Pe and IWR in that province.

3.4 An examination of how climate parameters affect productivity

3.4.1 Average Temperature to Productivity

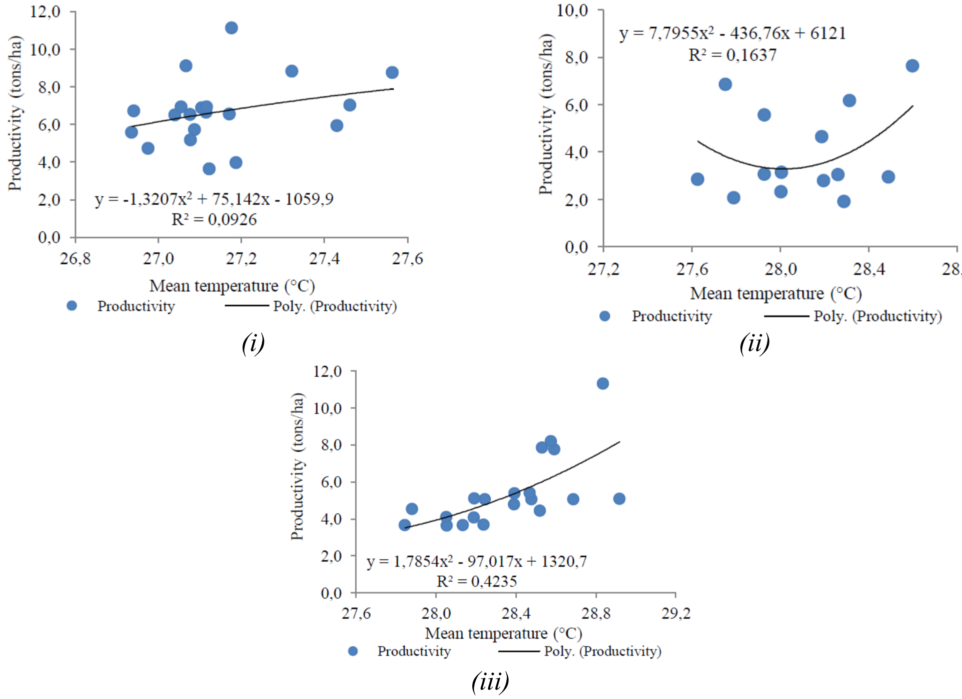
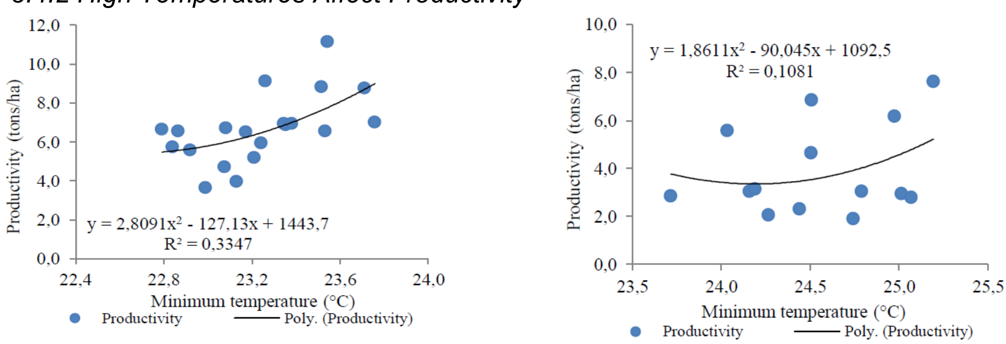


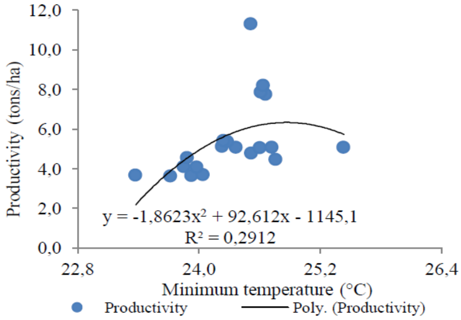
Fig. 13. Regression maize production and mean temperature; (i) West Sumatra; (ii) North Maluku; (iii) East Java

The polynomial regression analysis presented in Fig. 13 shows a weak to moderate relationship between mean temperature and maize yield, with temperature variability accounting for only 9–42% of the observed production fluctuations. These relatively low R^2 values suggest that temperature is not a primary determinant of maize productivity in the study areas. As Sinaga [13] notes, factors such as crop variety, soil nutrient availability, and cultivation practices exert greater influence on yield outcomes. Furthermore, Ahmad et al. [14] demonstrated that adopting heat-tolerant varieties and implementing balanced fertilization strategies can effectively mitigate the adverse effects of climate change. Thus, while temperature plays a role in crop physiology, its isolated impact on overall maize production appears limited.

3.4.2 High Temperatures Affect Productivity

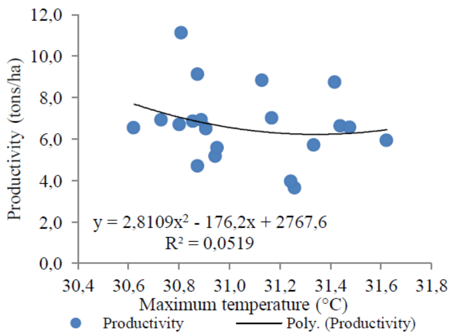


(i) *(ii)*

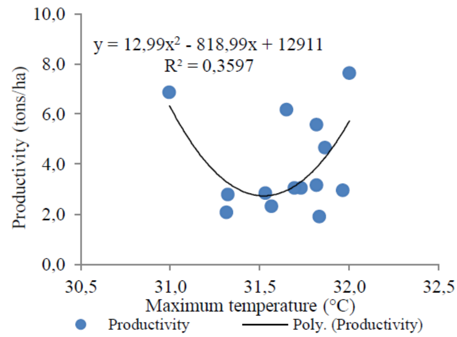


(iii)

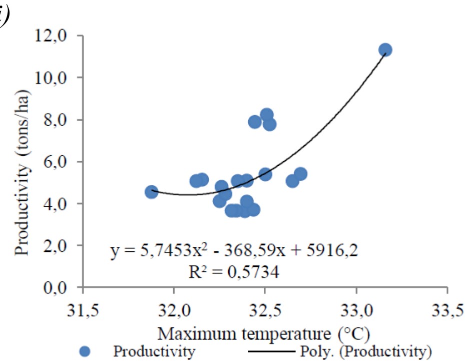
Fig. 14. Analysis of the regression between maize productivity and the minimum temperature; (i) West Sumatra; (ii) North Maluku; (iii) East Java



(i)



(ii)



(iii)

Fig. 15. Analysis of the regression between maize productivity and the highest temperature; (i) West Sumatra; (ii) North Maluku; (iii) East Java

To assess the effects of thermal extremes on maize productivity, both minimum and maximum temperatures were examined. The results, shown in Figs. 14 and 15, indicate weak to moderate correlations between temperature extremes and yield. Minimum temperature variations explain approximately 10–33% of yield variability, while maximum temperature changes account for 5–57% of production fluctuations. These findings suggest that extreme temperature conditions have a measurable but moderate impact on maize yields.

Although temperature regulates fundamental physiological processes such as transpiration and photosynthesis, brief periods of extreme heat or cold do not necessarily translate into substantial yield reductions. When adequate water and nutrients are available, crops can often withstand short-term temperature stress and maintain stable growth and development. This resilience helps explain the moderate correlation strength observed in the analysis.

3.4.3 Productivity through Precipitation Effective

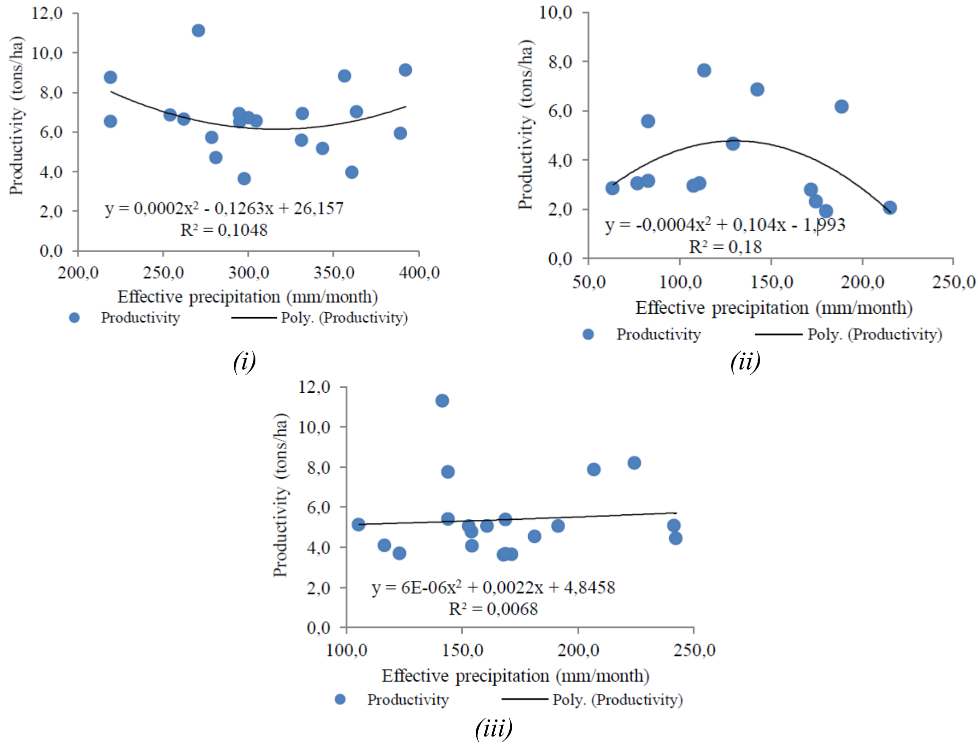


Fig. 16. Effective precipitation and maize productivity: a regression analysis; (i) West Sumatra; (ii) North Maluku; (iii) East Java

Figure 16 reveals a very weak correlation between effective precipitation and maize productivity, with R^2 values ranging from just 0.6% to 18%. This indicates that variations in effective rainfall explain only a small fraction of yield differences, suggesting that effective precipitation is not a dominant factor influencing maize production in these regions.

Nevertheless, Sulaminingsih et al. caution that altered rainfall patterns can significantly impact agricultural outcomes by increasing drought risk, particularly when water availability fails to meet crop demands during critical growth periods. Under such conditions, water deficiency can become a major yield-limiting factor. However, the influence of precipitation variability diminishes when supplemental irrigation is properly implemented. Wang et al. [14] demonstrated that regulated supplementary irrigation systems can enhance yields compared to purely rainfed agriculture. Similarly, Sirait et al. [15] emphasized that appropriate irrigation practices throughout all growth stages are essential for maximizing production.

Beyond water availability, maize productivity is strongly influenced by agronomic factors including cultivation techniques, nutrient management, and varietal selection [13]. The weak and context-dependent relationship observed between effective precipitation and yield reflects the complex interaction of these multiple factors, many of which exert greater influence on final production levels than rainfall alone.

4 Conclusion

This research demonstrates that the LARS-WG model performs well in reproducing Indonesia's climatic conditions, especially in East Java, West Sumatra, and North Maluku. These results indicate that LARS-WG is suitable for use in future climate projection analyses within the Indonesian context. The amount of irrigation water required for maize production is determined not only by effective rainfall but also by the crop's developmental stage. Ensuring that irrigation is applied in accordance with each growth phase is crucial for improving yield and maximizing productivity. The Pearson correlation results show that extreme temperature variations significantly influence irrigation water demand, whereas mean temperature has no meaningful effect. In addition, effective precipitation contributes to shaping irrigation needs.

The polynomial regression analysis further indicates that extreme temperature conditions have a significant effect on maize yield, while average temperature and effective rainfall do not exert a statistically significant influence. To strengthen food security in the long term, similar evaluations should be extended to other maize-producing regions by applying the LARS-WG model for climate projections. Subsequent studies may also explore different modeling techniques for yield prediction and design adaptive cropping patterns and irrigation management plans based on projected climate scenarios, while incorporating land suitability and irrigation system capacity considerations.

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